

Asymmetric Information Arrival and the Short-Run Dynamics of Australian Dollar Volatility: a Mixture of Distributions Approach

Terry Boulter

School of Economics and Finance

Queensland University of Technology

Abstract

Contemporary commentators point to excess volatility within the FX market as an indicator of market inefficiency. It is thought that the excessive volatility is being driven by speculation. Policy options have emerged which focus on bounding volatility via government regulation of speculation. These options make implicit assumptions; one, that volatility is excessive and two, that it is speculation which is driving volatility. What is not sufficiently understood is the role public information arrival plays in terms of explaining returns and its volatility impact. It is the purpose of this paper to simply model Australian Dollar returns and volatility with public information arrival, which has been classified into categories so as to ascertain whether total information arrival or the arrival of specific types of information is related to changes in returns and volatility. We use an EGARCH model so as to pick up the asymmetric impacts of good and bad news. We find evidence from both a GARCH and EGARCH model that public information plays an important role in the determination of AUD returns and volatility and that good news impacts are less than negative ones. We also find that economic information in relation to full information set has a greater relationship to volatility. This has some interesting implications in terms of the volatility debate. Rather than regulating speculation, it may be more relevant to clarify information.

1. Introduction

Since the collapse of the fixed exchange rate system (August 1971), the global foreign exchange (FX) market has been in a state of intense expansion and evolution. This truly global market has been able to internalise an extraordinary amount of capital growth, while simultaneously experiencing unprecedented levels of market wide volatility (Hasan and Wallace (1996)). In 1998, transactions were more than 130 times greater than they were in 1973. FX transactions are now in excess of 50 times the total value of all international trade in goods and services. Daily turnover is estimated at 1.3 trillion US dollars per day.¹ Massive liquidity, coupled with the tremendous volume of transactions, linked to the technological ease and speed in which these transactions take place, has resulted in a highly volatile market with global ramifications. It has been argued that volatility has reached a state where it has become excessive, warranting government intervention.² Before effective policy can be put in place a thorough understanding of the causes of volatility is essential (Collinge (1994)).

Researchers have taken a number of different tacts in their attempts to understand foreign exchange market volatility. Rose (1994) has focused on the connection between economic fundamentals and foreign exchange volatility, De Grauwe, Dewachter and Embrechts (1993) and Rao (1993), have attempted to use chaotic models to explain foreign exchange volatility, Frankel and Froot (1987), have used expectations and survey data to examine volatility. Recent research by Andersen, Bollerslev, Diebold and Labys (1999), has focused on model free estimates of exchange rate volatility and correlations with interesting results. Results in general however have been mixed and irresolute. One area of research that has been particularly fertile has been the examination of the relationship between volatility and information arrival. Frankel (1981), Goodhart and Smith (1985), Hakkio and Pearce (1985), Bollerslev and Melvin (1994), Hogan and Melvin (1994) Melvin and Tan (1996) have all modelled volatility in relation to information arrival with interesting

¹ For an excellent statistical coverage of the foreign exchange market see, Bank for International Settlements, Monetary and Economic Department, Central Bank Survey of Foreign Exchange and Derivatives Market Activity 1998, which can be located at: www.rba.gov.au/media/mr_98_12.html

² For good coverage of this issue see Collinge (1994), Eichengreen, Tobin and Wyplosz (1995), Barber and Taylor (1995) and Kenen (1995).

results. These studies have been limited however, in that they focus only on the effects of a finite number of macro economic type announcements, which occurred at specific points in time. Such studies focus on volatility around the time of an announcement and thus only reflect the market at that particular instant in time. Within this paper we attempt to model Australian Dollar volatility in relation to public information arrival within a high-frequency setting where the continuous 24-hour nature of the market is captured. The data that we use is tick by tick observations of the Australian dollar (AUD), for the period 1996. As will be seen in Section 3 of this paper, the AUD exchange rate is typical of most continuous financial time series data. It has a distinct trend, is non-normally distributed, and exhibits strong characteristics of Engle's (1982) Autoregressive Conditional Heteroskedasticity (ARCH) process. An interesting explanation for the presence of ARCH has been based on a hypothesis, which postulates that returns are generated by a mixture of distributions, with the rate of daily information arrival being the stochastic mixing variable. A number of researchers including Diebold (1986), Diebold and Nerlove (1989), Gallant et al. (1991), Stock (1987, 1988), Lamoureux and Lastrapes (1990) and Laux and Lilian (1993) have hypothesised that autocorrelation which is present within the time-varying rate of information arrival is what leads to the time-series dependencies in the conditional volatility of returns that are well specified by Generalised Autogressive Conditional Heteroskedasticity (GARCH)³ models. The testing of this hypothesis provides a good opportunity to estimate the impact that information arrival may have in terms of exchange rate volatility. In this paper we similarly motivate our use of ARCH models via the mixture of distributions framework so as to estimate information impacts on AUD return volatility. We also broadly classify information into subcategories (ie. Economic, Political, Social, Disaster, Other) in an attempt to determine whether specific categories of information plays a more or less significant role in terms of AUD volatility. Section 2 of this paper provides the theoretical motivation for the empirical analysis. Specifically we develop the mixture of distributions model, and a model of how returns for the AUD are generated. We then combine the two in order to formulate our conditional variance equations for the AUD. In Section 3 we describe the data, Section 4 discusses the empirical results, and

³ Techniques developed in the 1980s (Engle (1982), Bollerslev (1986) Nelson (1991)) give us the econometric tools for making predictions of future time-varying volatility.

Section 5 contains concluding remarks, and a discussion of the policy implications of our findings.

2. An Asymmetric Mixture of Distributions ARCH Model

Financial time series, which includes foreign exchange tick by tick data, has consistently be shown to have both structure within the volatility, and to have characteristic contiguous periods. In terms of contiguous periods, Mandelbrot (1963) has observed that financial time series data, which has large changes in price, is generally followed by large changes of either sign, while smaller changes are similarly followed by small changes in either sign. In terms of structure within the volatility, the autoregressive conditional heteroskedasticity (ARCH) process of Engle (1982) has been show by Bollerslev et al. (1992), to be a good model which captures the autoregressive nature of the volatility. The Generalised ARCH (GARCH) model of Bollerslev (1986) generalises the ARCH process by expressing the conditional variance h_t^2 as a linear combination of p lags of the squared residuals from the conditional mean equation plus q lags of the conditional variance equation h_t . The generalised formula for the conditional mean can be expressed as:

$$r_t = \alpha_0 + \sum_{i=1}^p \alpha_i r_{t-i} + \varepsilon_i \quad (1)$$

and the generalised conditional variance of those returns can be written as:

$$h_t^2 = \beta_0 + \sum_{i=1}^p \beta_i \varepsilon_{t-i}^2 + \sum_{i=1}^q \mathcal{M}_{t-i}^2 \quad (2)$$

where r_t represents the rate of return, $\alpha_0 + \alpha_i r_{t-i}$ is a conditional mean, because it is conditioned on the previous value (or values of r_t) with ε_i being the residuals. We interpret the residuals as reflecting unanticipated innovations in price. Positive changes (an unexpected increase in price) suggests that the innovations are “good news”, while negative changes (an unexpected decrease in price) suggest that the innovations are “bad news”. Additionally, a large value of $|\varepsilon_i|$ suggests that the innovation is “significant” in that it produces a large unexpected change in price. The conditional variance is estimated as a function of a constant β_0 , plus a combination of p lags of the squared residuals (innovations) of the conditional mean equation plus q lags of the conditional variance. Empirically, GARCH models as described above have been very successful. Of these models, the GARCH (1,1) is a preferred model

for explaining volatility (see the survey by Bollerslev et al. (1992)). ARCH and GARCH models however fail to capture some important properties of the data. The first being that these models do not allow for the asymmetric impact that innovations may have on volatility.⁴ As has been shown by Nelson (1991) and Schwert (1990) good innovations appear to have less of an impact on volatility than do negative ones of similar magnitude. A properly specified model of volatility would thus need to capture this important property of the innovation process. One approach that is able to capture asymmetric properties of the innovations is the EGARCH or Exponential GARCH model introduced by Nelson (1991). The specification of conditional variance is:

$$\log(h_t) = b_0 + b_1 \log(h_{t-1}) + b_2 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + b_3 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \quad (3)$$

In this model, good news, and bad news have different impacts on conditional variance. The model implies that the leverage effect (ie. b_3) is exponential, and that forecasts of the conditional variance will be nonnegative. The presence of the leverage effect can then be tested by the hypothesis that $b_3 < 0$.

The second issue relating to ARCH models is the lack of understanding of the dynamics of the structure within conditional volatility. One possible explanation is provided by the mixture of distributions hypothesis (MDH). The MDH is associated with Clark (1973) and Tauchen and Pitts (1983). The essence of MDH is that price changes over discrete periods of time are the sum of a random number of individual increments to price, where the random number depends on the rate of information arrival over the interval.

As a way of motivating our understanding of the mixture of distributions model, let \square_{it} denote the it th period equilibrium price increment. Variance can thus be written as:

$$\varepsilon_t = \sum_{i=1}^{n_t} \delta_{it} \quad (4)$$

where n_t is the mixing variable, representing the stochastic rate at which information arrives to the market. In other words, \square_t is drawn from a mixture of distributions

⁴ Within the literature, most researchers define this characteristic as the “leverage effect”.

where the variance of each distribution depends upon information arrival time. Equation (4) implies that daily returns are generated by a subordinated stochastic process, in which ε_t is subordinate to ε_{it} and n_t , with n_t being the directing process.⁵ If ε_{it} is i.i.d. with a mean of 0 and a constant variance σ^2 and the number of increments is sufficiently large, then $\varepsilon_t | n_t \sim N(0, \sigma^2 n_t)$. Lamoureux and Lastrapes (1990) and Laux and Ng (1993) show how the a mixture of distributions model provides an economic rationale for GARCH modelling. They explain GARCH in returns as a manifestation of time dependence in the rate of evolution of equilibrium returns. For example, assume that information arrival is serially correlated, expressed as:

$$n_t = k + b_{n_{t-1}} + \mu_t \quad (5)$$

where k is a constant and b a coefficient of serial correlation and μ_t an error term. If we assume $\Omega_t = E(\varepsilon_t^2 | n_t)$ is true (which states that the expected variance of returns is conditional upon information arrival), then the expected variance, which is dependent upon the stochastic process of information arrival, will be $\Omega_t = \sigma^2 n_t$. Substituting the moving average representation of equation (5) into this expression for variance results in;

$$\Omega_t = \sigma^2 k + b\Omega_{t-1} + \sigma^2 \mu_t \quad (6)$$

Equation (6) stipulates that the expected variance in returns is equal to some constant level of variance, plus a level of variance that is dependent upon the variance from the previous period plus a variance error. This model captures the structure within the conditional variance that is picked up when estimating volatility models. The structure is the time dependence component in the rate of evolution of equilibrium returns, which is being directed by information arrival. In order to incorporate the mixture of distribution framework within the context of explaining information impacts on AUD returns, we first develop a model of how those returns are generated within the foreign exchange market.

⁵ See Clark (1973)

3. Modelling AUD returns within the Mixture of Distribution Framework with Asymmetric Innovations.

Within the foreign exchange market there are N traders who as market makers buy and sell currency. The aggregate of these trades result in a sequence of market equilibrium that changes over time. The unit of time used in this paper is hourly, which we arrive at by aggregating tick by tick data within each hour for every hour of the year of 1996. The change from one equilibrium to the next is the result of information arrival. The arrival of information is random and occurs at inconsistent time intervals. The length of time it takes to move from one equilibrium to the next, is time varying, due to the nature of the information arrival process. At any one equilibrium point the desired position of an individual trader is:

$$P_t = \alpha(s_n - s) \quad (7)$$

where \mapsto is a positive constant, s_n is the n th traders reservation spot exchange rate which is arrived at by the traders perception of what the “true” value of the currency is. s is the current spot rate. If the current spot rate is less then the trader’s reservation spot price, then the trader believes the spot rate to be undervalued and thus expects it to appreciate. The trader in this situation will take a long position in the currency. If the current spot rate is greater that what the trader’s reservation spot rate is, then the trade believes the spot rate is overvalued and thus anticipates that it will depreciate. The trader in this situation will hold a short position. Each individual trader’s reservation spot rate will be unique to that trader. It will be influenced by their expectation of what the future value will be, (based on their “reading” of the market), the extent to which they have access to private information, (which would relate to their customer order flow), and finally it will be a function of the specific market model that they employ to arrive at their reservation rate. Market equilibrium will require that the total of all the traders’ long and short positions net to zero, which can be formally expressed as;

$$\sum_{n=1}^N P_t = 0 \quad (8)$$

and the market is cleared by the average of reservation spot rates so that the spot rate for the n th equilibrium is given as:

$$S = \frac{1}{N} \sum_{n=1}^N S_n \quad (9)$$

The market moves from one equilibrium to the next as the market receives more information. Information arrival changes the traders' view of what the "true" value of the currency is. The new view induces a re-evaluation of the reservation spot rate. Whether the trader then revises their long or short position depends on whether their new view results in a perception of the currency at that time as being over or under valued. The resulting change in the spot rate will thus be the average of the changes of all traders' reservation exchange rate, assuming that the within-hour increments to the market rate are normally distributed with a mean of zero and a constant variance. This can be represented as:

$$ds_i = \frac{1}{N} \sum_{n=1}^N ds_{in}, ds_i \equiv N(0, \sigma_i^2) \quad (10)$$

Where:

ds_i = change in market spot rate

ds_{in} = change in the n^{th} trader's reservation spot exchange rate

If we use I to represent the actual number of within-hour information events, which give rise to the trader's revised reservation rate, and if I is both random and time varying then we can rewrite equation (4) as:

$$ds = \frac{1}{N} \sum_{n=1}^N ds_i, ds \equiv N(0, \sigma^2, I) \quad (11)$$

The hourly price change is thus modelled as a mixture of independent normals with mixing variable information denoted as I . By subscripting I with a t which denotes hour, the hourly time series of I_t is obtained. I_t is the time series of hourly news headlines crossing the Reuters screen. This time series, is used to proxy information arrival. News arrival is significantly influenced by the day of the week, time of the day, and which market happens to be open at a particular point in time. The consistently occurring pattern implies that there will be autocorrelation within the time series. If first-order autocorrelation is assumed so that:

$$I_t = \alpha + bI_{t-1} + u_t \quad (12)$$

then the variance of the change in the US-AUD exchange rate (ds_t) conditional on hourly news arrival I_t ($h_t = \sigma^2 I_t$) is:

$$h_t = \sigma^2 \alpha + b h_{t-1} + \sigma^2 u_t \quad (13)$$

We can use equation (13) as a foundation for our volatility models of innovations within the mixture of distribution framework with information arrival as the mixing

variable. In this paper we are explicitly estimating the effect that innovations in the information arrival process have on the volatility of the AUD/ US dollar rate of exchange. We classify information into transparent categories⁶ so as to determine whether different classifications of information have different impacts on volatility. We estimate two models. One is a simple GARCH (1,1), with information arrival within the mean of the conditional variance equation;

$$h_t = b_0 + b_1 \varepsilon_{t-1}^2 + b_2 h_{t-1} + b_3 I_{t-1} \quad (14)$$

and the second being a EGARCH (1,1) that is able to pick up the asymmetric impacts of information arrival, again within the mean of the conditional variance, as expressed in the following functional form:

$$\log(h_t) = b_0 + b_1 \log(h_{t-1}) + b_2 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + b_3 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + b_4 I_{t-1} \quad (15)$$

where in both forms;

- I = all information
- I_{e1} = all economic information
- I_{e2} = broadly economic
- I_{e3} = currency information
- I_{e4} = trade information
- I_{e5} = money information
- I_{e6} = market information
- I_p = political information
- I_s = social information
- I_d = disaster information
- I_o = other information.

4. The Data

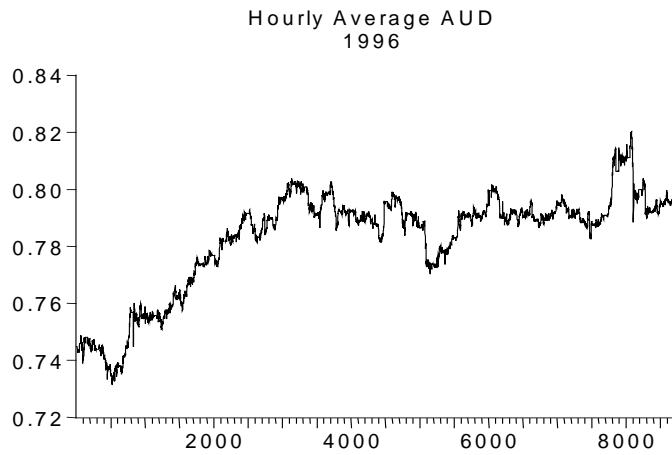
The data within this study is comprised of exchange rate data, foreign exchange returns data and news headline data. The unit of time used in the analysis is hourly. There are 8784 hours in a year. All three series are averaged to an hourly observation as per equation (16).

⁶ See Appendix A

$$\bar{X} = \frac{\sum_{i=1}^n X_i}{n} \quad (16)$$

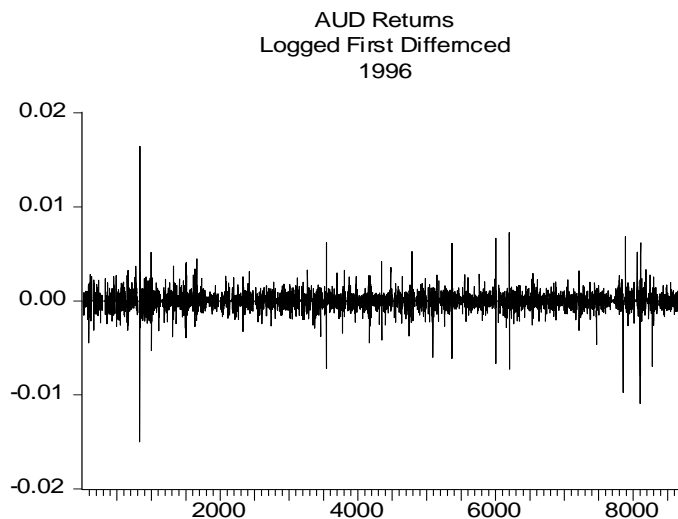
The exchange data is comprised of tick-by-tick observations of the U.S. Dollar price of an Australian Dollar (AUD) as displayed by Reuters from 1 January 1996 to 31 December 1996. Figure 1 is a graphical representation of the data based on an hourly average of the midpoint between the bid and ask rate, over the entire year of 1996. The data within this period trends upward, with the currency appreciating from approximately \$0.74 US/AUD to approximately \$0.79 over the year.

Figure 1



The AUD returns data is defined as the log difference of the hourly average of the midpoint between the bid and ask rate. Figure two is a plot of the returns data series.

Figure 2



Appendix B reports the summary statistics of the return series. Returns have a mean close to zero, they are negatively skewed, and are significantly more peaked than a normal distribution. The Jarque-Bera statistic confirms that the returns data are not normally distributed. The data exhibits characteristics of heteroskedasticity. The Lagrange Multiplier (LM) test developed by Engle (1982) is used to test the null hypothesis of no autoregressive conditional heteroscedasticity (ARCH). ARCH effects are present when the conditional variance of the time series is time varying. The presence of ARCH supports the use of techniques in the Autoregressive Conditional heteroskedasticity (ARCH) family which are robust to non-normality. The results of the LM ARCH test are displayed in Table 1.

Table 1
Lagrange Multiplier (ARCH) Test Results
Returns

	F-Statistic	Probability
LM Test	60.45831	0.00000

The LM test confirms that there are ARCH effects within the returns data.

The information variable is proxied by the number of news headlines reported on the Reuters Money market Headline News screen for the same time period as the returns data. There were a total of 168,043 headlines for the year of 1996. Because we want to know whether specific types of information are related to varying degrees of volatility, we have decomposed the total headline data set into subcategories. This was done by using a simply program⁷ that searches each headline for specific words that occur in a predefined dictionary. The program then tallies the total number of words in each headline associated with a category and classifies the headline as being either Economic, Political, Social, Disaster or Other. There is also a subcategory classification for Economic into Broad Economic, Currency, Trade, Market and Money. A copy of the Dictionary is attached, as Appendix A. Figure 3 is a graphical

⁷ The program was developed in MATLAB© with the invaluable support of Mark Berry of Information Technology Services, Queensland University of Technology.

representation of average hourly news arrival by category for a typical week during the year.

Figure 3

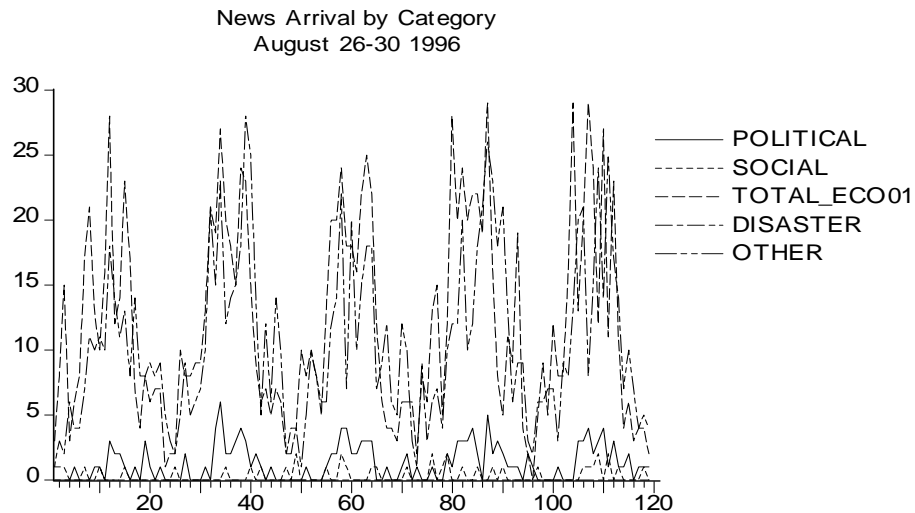


Figure 3 demonstrates that there exists a distinct intra-daily pattern where news events climb to a daily peak as the European and North American markets overlap. The LM ARCH test as shown in Table 3 confirms that the information series also has ARCH effects.

Table 3

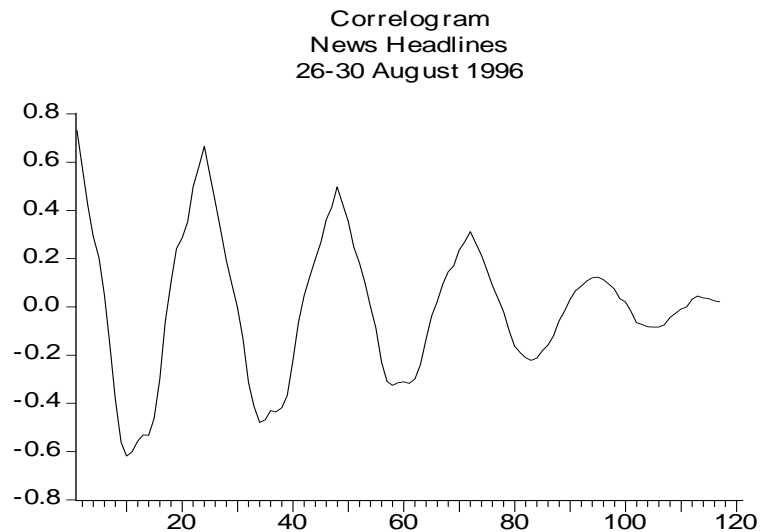
Lagrange Multiplier (ARCH) Test Results

News Headline Data

	F-Statistic	Probability
LM Test	1105.071	0.00000

The need for seasonal adjustment is demonstrated by the autocorrelation pattern for each series as is represented in the Figure 4. This pronounced seasonality requires adjustment before any statistical inference can be made (Dacorogna, M.M., et al. 1993).

Figure 4



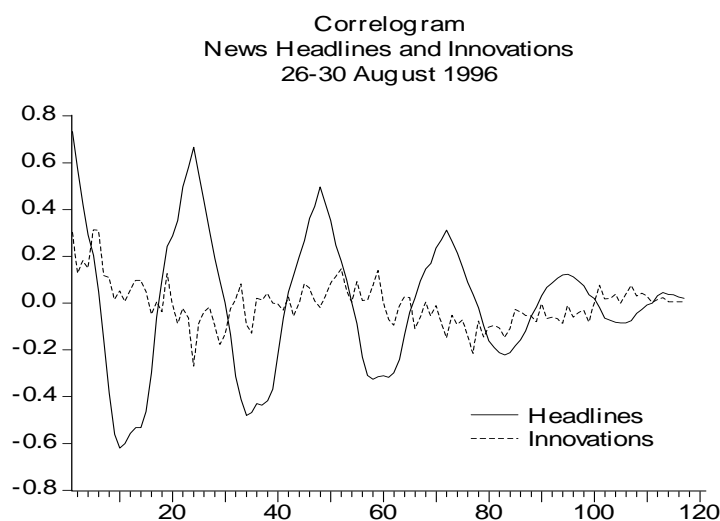
The New Headline data exhibits strong seasonality across the hours of the day, and the days of the week. This reflects changes in market activity as the market opens and closes, across international time zones. For example the greatest amount of activity occurs at hour 24, 48 72, etc., times at which both the London and New York markets are open.⁸

Seasonal adjustment of the data is accomplished by constructing a system of 23 dummy variables each representing the hourly impact on price. These coefficients are then estimated by regressing them against returns. The residuals from this equation are then captured as a representation of hourly information innovations.

Figure 5 and 6 depict the autocorrelations of the raw data and the seasonally adjusted data, which shows that the previously pronounced patterns over the business week are largely removed. We use these captured “innovations” as our proxy for public information arrival for each information set. We view this data set as a representation of the nonsystematic arrival of information to the market.

⁸ For purposes of identifying the regional business hours in terms of GMT, the following hours may be used as indicative of 8am to 4pm in each of the regional centres; Tokyo/Sydney, 2300-0700; London, 0800-1600; and New York, 1300-2100.

Figure 5



5. Informational Arrival and Exchange Rate Dynamics

There is a large body of theoretical literature that links public information arrival to pricing and to volatility of financial assets. An important and growing strand of that literature is related to microstructure theory. The increased availability of detailed, real time tick-by-tick data allows for empirical investigation at a level of detail that has previously been very difficult. O'Hara (1995), provides a good coverage of microstructure theory and models that link information arrival to market activity.

One of the important threads that links microstructure models to one another is the data being modelled. Financial time series, which includes our foreign exchange returns data, exhibits structure within the volatility, and has characteristic contiguous periods. Mandelbrot (1963) noted that large changes in asset prices were followed by large changes of either sign, while small changes were followed by small changes. The autoregressive conditional heteroskedasticity (ARCH) process of Engle (1982) has been shown by Bollerslev (1986), to be a good description of these characteristics. A good review of the ARCH literature is provided by Bollerslev et al. (1992). A number of researchers including, Diebold (1986), Diebold and Nerlove(1989), and Gallant et al. (1991) theorise that the autocorrelation within financial time series is being generated by a mixture of distributions, in which the rate of daily information arrival is the stochastic mixing variable. Testing of this proposition has taken two

tacts. Adopting an indirect approach, Engle, Ito and Lin (1990) and Ito, Engle and Lin (1992) have found that volatility in one geographic market is transmitted to other markets in a “meteor-shower” type fashion. They assume that the increased volatility is due to an increased rate of information arrival. These researchers use these finding to indirectly support the mixture of distribution explanation.

Using a direct test Lamoureux and Lastrapes (1990) use daily trading volume as a proxy for information arrival as the mixing variable. They find that when the usual GARCH specification is adjusted to include a volume regressor, (representing information arrival) the GARCH effects are largely removed. They conclude that ARCH and GARCH effects are a manifestation of the daily time dependence in the rate of information arrival. Our paper is thus similarly motivated in using a GARCH and an EGARCH model. Unlike Lamoureux, and Lastrapes we additionally wish to determine whether specific types of information can be related to AUD volatility. We are also interested in determining whether there is a leverage effect present within our information variables.

6. *Classified Information Arrival, Exchange Rate Returns and Volatility*

Using hourly AUD returns data, we start by estimating a GARCH (1,1) model without including an information variable. The model taking the following form:

$$\begin{aligned} ds_t &= \alpha + \varepsilon_t \\ h_t &= b_0 + b_1 h_{t-1} + b_2 \varepsilon_{t-1}^2 \end{aligned} \quad (17)$$

We first wish to determine whether a GARCH model is a good model of AUD volatility. Table 4 reports the estimate of this model, which confirms that a statistically significant amount of the conditional variance in returns is being explained by a GARCH process.

Table 4
GARCH (1,1) Estimate of Returns

$$\begin{aligned} ds_t &= \alpha + \varepsilon_t \\ h_t &= b_0 + b_1 h_{t-1} + b_2 \varepsilon_{t-1}^2 \end{aligned}$$

	Coefficient	Std. Error	z-statistic	Probability
Mean Equation				
Constant (α_0)	-1.73 x 10 ⁻⁵	1.73 x 10 ⁻⁵	-0.997229	0.3187

	Coefficient	Std. Error	z-statistic	Probability
-0Conditional Variance				
Constant (b_0)	6.55 x 10 ⁻⁸	2.48 x 10 ⁻⁸	2.639859	0.0083
ARCH(1) (ε^2_{t-1})	0.150000	0.008037	18.66419	0.0000
GARCH(1) (h_{t-1})	0.600002	0.007654	78.39193	0.0000
Overall Model				
R-Squared	-0.001020			
Log Likelihood	50505.17			

These findings are consistent with findings reported by Bollerslev et al. (1992). We are also interested to ascertain whether information arrival can help to explain AUD returns with the GACRH process explaining the volatility. In order to examine this proposition we estimate a new model with the rate of information arrival as proxied by the captured innovation procedure, being entered into the mean equation of returns. The new GARCH model, taking the following form:

$$\begin{aligned}
 ds_t &= \alpha + \varepsilon_t \\
 h_t &= b_0 + b_1 h_{t-1} + b_2 \varepsilon_{t-1}^2 + b_3 I_t
 \end{aligned}
 \tag{18}$$

With this model we hope to examine whether the addition of the information variable helps to explain AUD returns. Table 5 reports these results.

Table 5
GARCH (1,1) Estimate of Returns
With Information

$$\begin{aligned}
 ds_t &= \alpha + \varepsilon_t \\
 h_t &= b_0 + b_1 h_{t-1} + b_2 \varepsilon_{t-1}^2 + b_3 I_t
 \end{aligned}$$

	Coefficient	Std. Error	z-statistic	Probability
Mean Equation				
Constant (α_0)	-2.48 x 10 ⁻⁵	1.74 x 10 ⁻⁵	-1.428537	0.1531
INNO_TOT_HL (I)	3.47 x 10 ⁻⁶	1.25 x 10 ⁻⁶	2.784149	0.0054
Conditional Variance				
Constant (b_0)	6.27 x 10 ⁻⁸	2.49 x 10 ⁻⁸	2.517782	0.0118
ARCH(1) (ε^2_{t-1})	0.150000	0.008044	18.64845	0.0000
GARCH(1) (h_{t-1})	0.600002	0.007649	78.44472	0.0000
Overall Model				
R-Squared	-0.004443			
Log Likelihood	50367.95			

The information variable (I) does enter significantly into the mean equation for conditional variance in returns and our GARCH effect remains consistent. This suggests that volatility of AUD returns is a function of the residuals from the condition mean equation plus, these residuals lagged one period, and that returns are significantly impacted upon by innovations from the information arrival process. We then test to see whether specific types of information, such as economic and its subcategories, plus, political, social, disaster, etc., as categorised by the dictionary procedure was able to provide any additional insights into AUD returns. Table 6 reports these results.

Table 6
GARCH (1,1) Estimate of Returns
With Information Categories

$$h_t = b_0 + b_1 \varepsilon_{t-1}^2 + b_2 h_{t-1} + b_3 I_t$$

	Independent Variable	Coefficient	Std. Error	z-Statistic	Probability
I	All Information	3.47×10^{-6}	1.25×10^{-6}	2.784149	0.0054
I_{e1}	All Economic Information	6.23×10^{-6}	2.31×10^{-6}	2.703573	0.0069
I_{e2}	Broadly Economic	2.87×10^{-5}	1.47×10^{-5}	1.951404	0.0510
I_{e3}	Currency	-6.24×10^{-6}	6.03×10^{-6}	-1.035561	0.3004
I_{e4}	Trade	1.83×10^{-5}	1.60×10^{-5}	1.147184	0.2513
I_{e5}	Money	1.75×10^{-5}	4.31×10^{-6}	4.052178	0.0001
I_{e6}	Market	-3.42×10^{-5}	2.93×10^{-5}	-1.166544	0.2434
I_p	Political	3.41×10^{-5}	1.09×10^{-5}	3.120882	0.0018
I_s	Social	2.03×10^{-5}	3.15×10^{-5}	0.643857	0.5197
I_d	Disaster	-3.13×10^{-5}	0.000107	-2.292569	0.7699
I_o	Other	4.17×10^{-6}	2.84×10^{-6}	1.467615	0.1422

It is interesting to note that the aggregate economic information category (I_{e1}) is statistically significant having a marginally larger coefficient than the total information category (I) of which (I_{e1}) is a component. This may indicate that there is information within the total information category (I) which may not be relevant in terms of returns. This may be the result of the variable defined as Currency (I_{e3}),

Trade (I_{e4}), Market (I_{e6}), Social (I_s), Disaster (I_d), and Other (I_o), not having statistically significant impacts on returns and thus distorts the impact of (I).

We now turn our attention to examining volatility of returns. Recognising that information arrival may have asymmetric impacts on volatility as demonstrated by Pagan and Schwert (1990) we estimate a simple EGARCH (1,1) model without any information variable. Our purpose is to ascertain whether there is a distinction between good news and bad news within AUD return volatility. We do find a leverage effect. Table 7 reports these findings.

Table 7
EGARCH (1,1) Estimate of Returns
With Information

$$ds_t = \alpha + \varepsilon_t$$

$$\log(h_t) = b_0 + b_1 \log(h_{t-1}) + b_2 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + b_3 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$$

	Coefficient	Std. Error	z-statistic	Probability
Mean Equation				
Constant (α_0)	2.56 x 10 ⁻⁵	7.28 x 10 ⁻⁶	3.520487	0.0004
Returns_1	0.143355	0.010374	13.81811	0.0000
Conditional Variance				
Constant (b_0)	-12.59490	0.154071	-81.74739	0.0000
b_2	0.328955	0.007969	41.28120	0.0000
b_3 (leverage)	-0.060554	0.005638	-10.74087	0.0000
EGARCH	0.140414	0.010518	13.35030	0.0000
Overall Model				
R-Squared	0.001970			
Log Likelihood	50944.43			

Having determined that leverage effects are present, we then estimate a model with information within the conditional variance equation to determine whether a EGARCH model with information arrival within the variance equation can help to explain AUD return volatility. Table 8 confirms that information arrival has a statistically impact on AUD volatility.

Table 8
EGARCH (1,1) Estimate of Returns
With Information

$$ds_t = \alpha + \varepsilon_t$$

$$\log(h_t) = b_0 + b_1 \log(h_{t-1}) + b_2 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + b_3 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + b_4 I_t$$

	Coefficient	Std. Error	z-statistic	Probability
Mean Equation				
Constant (α_0)	2.12 x 10 ⁻⁵	7.09 x 10 ⁻⁶	2.987444	0.0000
Returns_1	0.137884	0.010942	12.60151	0.0000
Conditional Variance				
Constant (b_0)	-13.00584	0.155300	-83.74658	0.0000
Leverage Effect	-0.044618	0.006495	-6.869063	0.0000
EGARCH	0.138611	0.010445	13.27050	0.0000
INNO_TOT_HL_2	0.092540	0.002186	42.32981	0.0000
Overall Model				
R-Squared	0.002884			
Log Likelihood	51057.39			

We then proceed to measure the impact that our categorised information variables have on AUD volatility using the EGARCH model. The results for our subcategory information variables in terms of their impact on AUD volatility are presented in Table 9.

Table 9
EGARCH Estimate of Returns
With Information Categories

$$\log(h_t) = b_0 + b_1 \log(h_{t-1}) + b_2 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + b_3 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + b_4 I_t$$

	Independent Variable	Coefficient	Std. Error	z-Statistic	Probability
I	All Information	0.092540	0.002186	42.32981	0.0000
I_{e1}	All Economic Information	0.050857	0.001727	29.45047	0.0000
I_{e2}	Broadly Economic	0.067355	0.002946	22.86535	0.0000
I_{e3}	Currency	0.037293	0.001380	27.02648	0.0000

I_{e4}	Trade	0.059757	0.002840	21.03953	0.0000
I_{e5}	Money	0.055330	0.001668	33.17349	0.0000
I_{e6}	Market	-0.023035	0.002819	-8.171972	0.0000
I_p	Political	0.005964	0.002756	2.163991	0.0305
I_s	Social	0.079019	0.002990	26.42472	0.0000
I_d	Disaster	0.018281	0.005280	3.462292	0.0005
I_o	Other	0.058385	0.002410	24.22141	0.0000

Our EGARCH results, indicate that there are persistent leverage effects across all the information variables, and that they have significant impacts on AUD volatility, except for our political information variable. It is interesting to note that the Social information variable has the largest coefficient. The dictionary terms which make up this category include words like, “conflict”, “confrontation” “threat”, “attack”, “defy” aggressive words that we anticipate have impacts on traders expectations. All of the Economic Information variables have significant impacts on AUD volatility, with “trade” and “money” having the largest coefficients. Unlike the estimates from our GARCH model of returns, the EGARCH, model of volatility finds the economic subcategory variables Trade (I_{e4}), Money (I_{e5}) and Market (I_{e6}) to be to be statistically significant. These variables appear not to impact on returns but do impact on volatility. Our Other (I_o) variable is also statistically significant within the EGARCH volatility framework and not within the GARCH returns framework. It is interesting to note that this coefficient is larger than the All Economic Information (I_{e1}) variable. This may indicate that the dictionary classification procedure has in some way sifted out irrelevant information leaving within the Other (I_o) category some classification of information worth further exploration.

7. Conclusion

Within this paper we have looked at the relationship between public information arrival and its impact on the exchange rate of the Australian dollar as motivated by the mixture of distributions hypothesis. The evidence suggests that there does exist a relationship between information arrival and AUD returns and volatility and that the impacts are asymmetric. Overall the evidence indicates that public information arrival plays an important role in the determination of AUD returns and that good news impacts are less than the negative news impacts. In fact these limited findings, which only relate to AUD volatility in 1996, appear to indicate that the exchange rate is

responding in a significant way to economic information. Both the GARCH and EGARCH models support these findings. This gives rise to an interesting issue in terms of AUD volatility. If it is economic information that is more closely associated with volatility, and if it is the case that this information is generally within the domain of government dissemination, then this in turn has some important implications in terms of the excess volatility debate. It may be the case that the government needs to clarify economic information, to make it better understood, more transparent, as a way or quelling exchange rate volatility. Regulators have generally assumed that excess volatility is a function of noise trading, which is largely self-generating and unrelated to new information. Our findings indicate that AUD returns for the year 1996, is a function of information arrival, and that information classified as economic plays a significant role in terms of influencing volatility. Until such time that robust evidence exists supporting claims of excess volatility which is driven primarily by noise trading which in turn can be shown to be reduced by raising costs of trading, one must question proposals for “*throwing sand in the wheels of international finance*”.

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Appendix A

Dictionary

ECONOMIC BROADLY ECONOMIC

01	Dow
01	Shares
01	Economic
01	Forex
01	FX
01	Industrial
01	Manufacturing
01	Services
01	Tax
01	Construction
01	Unemployment

CURRENCY

02	Baht
02	Currencies
02	Dlr
02	Baht
02	Euro
02	DEM
02	JPY
02	AUD
02	FRF
02	GBP
02	Spot
02	Sterling
02	Franc
02	Dollar
02	Mark
02	USD
02	CHF
02	CAD
02	Lira
02	Rupee
02	Peso
02	Riyal
02	Renminbi
02	Yen
02	Rand
02	Yuan
02	Swaps

TRADE

03	Trade
03	Balance_of_Payments
03	Current_Account
03	Export
03	Import
03	Trade
03	Reserves
03	Free-trade

MONEY

04 Money
04 Inflation
04 Interest_Rate
04 PCT
04 MONEY
04 M-2
04 M1
04 M2
04 M3
04 M4
04 Central_Bank
04 Yield
04 Loans
04 T-Bill
04 Bond
04 Bonds
04 Bank
04 Banks

MARKET

05 Market

POLITICAL

ARMY
BUDGET
CABINET
COMMUNIST
CONSTITUTIONAL
DEMOCRACY
ELECTORAL
EMS
EMU
EU
KING
KREMLIN
LEADER
LEADERS
LIBERAL
MINISTER
MINISTERS
MINISTRY
NATO
OPINION
OPPOSITION
PARLIAMENT
PARTIES
POLICY
POLITICAL
POLITICS
POLLS
PRIVATISATION
PRESIDENCY
PRESIDENT
PROTEST
REBELS
REFORM
SENATE
SOLIDARITY

SUMMIT
TAX
TAXATION
TAXES
VOTES
VOTERS

SOCIAL

CONFLICT
CONFRONTATION
COURT
DEFY
FORBIDDEN
POLICE
PROSECUTOR
PROTEST
RIOT
SOCIAL
STRIKE
THREAT
WORLD
JOBLESS
JUDGE
UNEMPLOYMENT
ATTACK

DISASTER

DISASTER
FLOOD
VOLCANO
EARTHQUAKE
FIRE
SHOOTING
STARVATION

OTHER

Appendix B

Summary Statistics of AUD Returns

Mean	7.34×10^{-6}
Median	0.000000
Standard Deviation	0.000771
Skewness	-0.391667
Kurtosis	62.96926
Jarque-Bera	1316325 (0.000000)

